

# III - Persistent homology

*PSL Week - Topological Data Analysis*

## Abstract

We explain how to track the homology groups to a whole *family* of spaces simultaneously, and how to summarize the result by a simple object with stability properties: the *persistence diagram*.

In a typical TDA pipeline, we start from a point cloud in a metric space, build a nested family (a *filtration*) of simplicial complexes, compute homology at all scales, and visualize how connected components, loops and higher-dimensional holes appear and disappear as the scale changes.

## Contents

<b>1</b>	<b>Filtrations of spaces and complexes</b>	<b>1</b>
1.1	Filtrations . . . . .	1
1.2	Filtrations of simplicial complexes . . . . .	2
<b>2</b>	<b>Persistence homology structures</b>	<b>2</b>
2.1	Modules . . . . .	4
2.2	Barcodes . . . . .	4
2.3	Diagrams . . . . .	5
<b>3</b>	<b>Bottleneck distance between diagrams</b>	<b>5</b>
3.1	Definition . . . . .	5
<b>4</b>	<b>Stability of persistence</b>	<b>6</b>
4.1	Stability of sublevel set filtrations . . . . .	6
4.2	Stability for point clouds . . . . .	7

## 1 Filtrations of spaces and complexes

### 1.1 Filtrations

The idea of a filtration is to look at a space  $X$  through a family of nested subsets, ordered by a parameter, often interpretable as a scale or time.

**Definition 1.1** (Filtration of a space). Let  $X$  be a topological space. A *filtration* of  $X$  indexed by a totally ordered set  $(T, \leq)$  (typically  $T = \mathbb{R}$  or  $T = \mathbb{N}$ ) is a family of subspaces  $(X_t)_{t \in T}$  such that:

- (i)  $X_s \subset X_t$  whenever  $s \leq t$ ;
- (ii)  $\bigcup_{t \in T} X_t = X$ .

**Example 1.2** (Sublevel sets of a function). Let  $f : X \rightarrow \mathbb{R}$  be continuous. For each  $t \in \mathbb{R}$ , define the *sublevel set*

$$X_t := \{x \in X : f(x) \leq t\}.$$

Then  $(X_t)_{t \in \mathbb{R}}$  is a filtration: if  $s \leq t$  then  $X_s \subset X_t$ , and  $\bigcup_t X_t = X$ . For instance, one can take  $f$  to be the height function on a surface embedded in  $\mathbb{R}^3$ .

**Example 1.3** (Offset filtration). Let  $X$  be a compact subset of a metric space  $(M, d)$ . Write

$$\text{dist}(y, X) := \inf_{x \in X} d(x, y)$$

for the distance from  $y$  to set  $X$ . For  $t \geq 0$  define the thickening

$$X_t := \{y \in M : \text{dist}(y, X) \leq t\}.$$

Then  $(X_t)_{t \geq 0}$  is a filtration.  $X_t$  is call the  $t$ -offset of  $X$  in  $M$ . See Figure 1 for  $X$  being a finite sample.

## 1.2 Filtrations of simplicial complexes

In computations we usually work with simplicial complexes rather than arbitrary spaces.

**Definition 1.4** (Filtration of complexes). A *filtration of simplicial complexes* is a family  $(\mathcal{K}_t)_{t \in T}$ , where each  $\mathcal{K}_t$  is a simplicial complex and

$$s \leq t \implies \mathcal{K}_s \subset \mathcal{K}_t$$

(as subcomplexes, i.e. at the level of simplices).

**Example 1.5** (Čech and Vietoris–Rips filtrations). Let  $\mathcal{P} \subset \mathbb{R}^d$  be a finite point cloud. For each  $\alpha > 0$  we defined in Chapter 2:

- the Čech complex  $\text{Cech}(\mathcal{P}, \alpha)$ ,
- the Vietoris–Rips complex  $\text{Rips}(\mathcal{P}, \alpha)$ .

As the scale  $\alpha$  increases, these complexes are nested:

$$\alpha \leq \beta \implies \text{Cech}(\mathcal{P}, \alpha) \subset \text{Cech}(\mathcal{P}, \beta), \quad \text{Rips}(\mathcal{P}, \alpha) \subset \text{Rips}(\mathcal{P}, \beta).$$

Thus  $(\text{Cech}(\mathcal{P}, \alpha))_{\alpha > 0}$  and  $(\text{Rips}(\mathcal{P}, \alpha))_{\alpha > 0}$  are filtrations. These are the main constructions used in TDA.

**Example 1.6** (Finite filtrations). In many practical situations we consider a *finite* increasing sequence of complexes

$$\mathcal{K}_0 \subset \mathcal{K}_1 \subset \cdots \subset \mathcal{K}_m,$$

for example obtained by sorting the simplices by some “time of appearance” (distance threshold, function value, etc.). We may take  $T = \{0, 1, \dots, m\}$  with the usual order.

## 2 Persistence homology structures

Given a filtration  $(\mathcal{K}_t)_{t \in T}$  of simplicial complexes, we can form homology at each index  $t$  to get a family of vector spaces  $H_k(\mathcal{K}_t)$  for each fixed dimension  $k$ . Because the complexes are nested, we also get linear maps between these spaces, induced by the inclusions. This structure is called a *persistence module*. It allows to keep track of how the sequence of homology groups evolves as a whole.

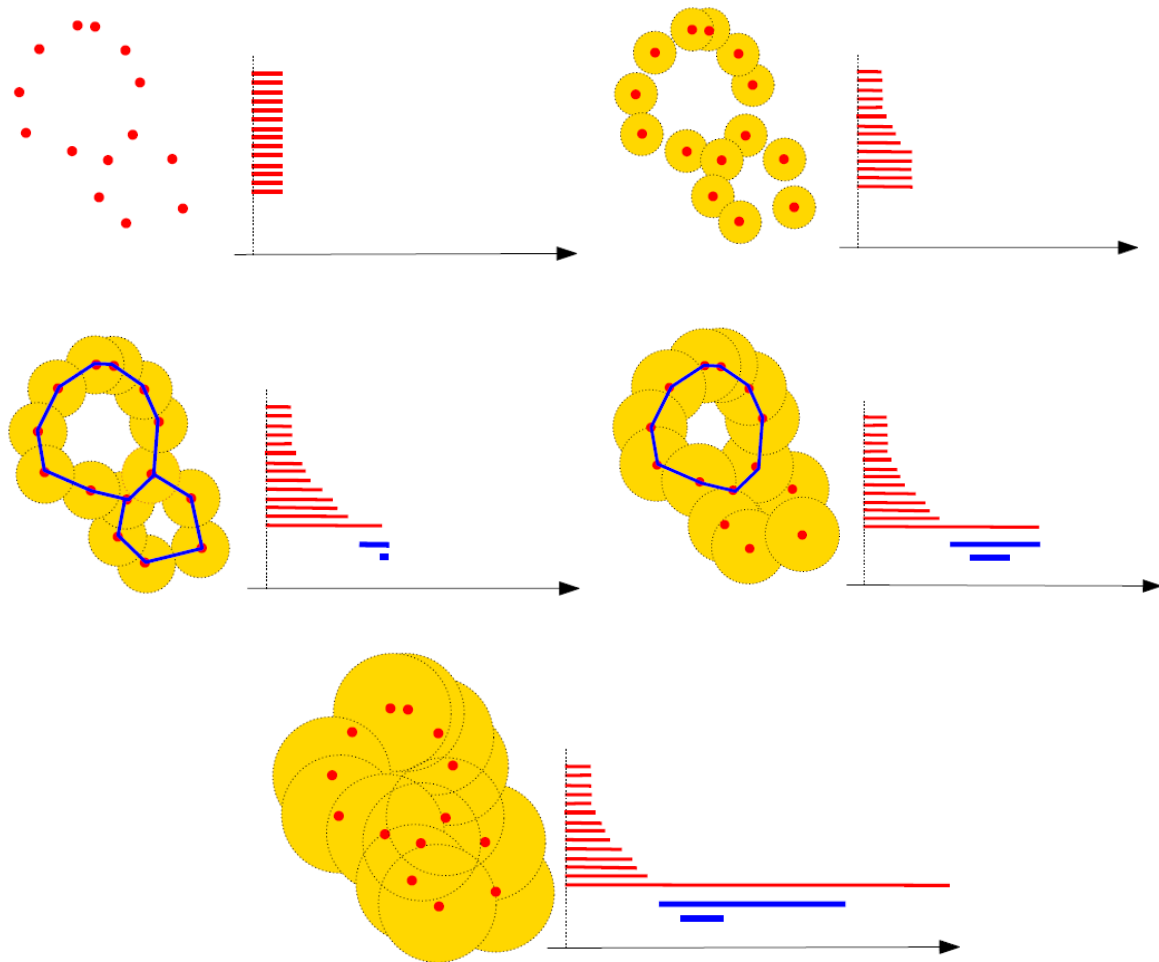


Figure 1: A point cloud on a circle and its Čech filtration at increasing scales  $\alpha$ , with associated barcodes of dimensions 0 (red) and 1 (blue).

## 2.1 Modules

Throughout this section we work over a fixed field  $\mathbb{F}$ , often  $\mathbb{F} = \mathbb{Z}/2\mathbb{Z}$  as in Chapter 2.

**Definition 2.1** (Persistence module). Let  $(T, \leq)$  be a totally ordered set. A *(homological) persistence module* over  $T$  (with coefficients in  $\mathbb{F}$ ) is:

- a family of  $\mathbb{F}$ -vector spaces  $(V_t)_{t \in T}$ ,
- for all  $s \leq t$  linear maps  $\varphi_s^t : V_s \rightarrow V_t$

such that:

- (i)  $\varphi_t^t = \text{id}_{V_t}$  for all  $t \in T$ ;
- (ii) for all  $r \leq s \leq t$ ,

$$\varphi_s^t \circ \varphi_r^s = \varphi_r^t.$$

You should think of  $V_t$  as the homology at “time”  $t$ , and  $\varphi_s^t$  as telling how classes at time  $s$  evolve when we go forward to time  $t$ .

**Example 2.2** (Homology of a filtration). Let  $(\mathcal{K}_t)_{t \in T}$  be a filtration of simplicial complexes. Fix a dimension  $k \geq 0$ .

For each  $t$ , let

$$V_t := H_k(\mathcal{K}_t; \mathbb{F}).$$

For  $s \leq t$ , the inclusion  $\iota_s^t : \mathcal{K}_s \hookrightarrow \mathcal{K}_t$  induces a linear map on homology

$$(\iota_s^t)_* : H_k(\mathcal{K}_s) \rightarrow H_k(\mathcal{K}_t).$$

Set  $\varphi_s^t := (\iota_s^t)_*$ . Functoriality of homology implies that this family satisfies the axioms of a persistence module. This is the central example in TDA.

$$\begin{array}{ccccccc} \{0\} & \xrightarrow{\varphi_0^1 = (0)} & \mathbb{F} & \xrightarrow{\varphi_1^2 = \begin{pmatrix} 1 \\ 0 \end{pmatrix}} & \mathbb{F}^2 & \xrightarrow{\varphi_2^3 = \begin{pmatrix} 0 & 1 \end{pmatrix}} & \mathbb{F} \\ \{0\} & \xrightarrow{\varphi_0^1 = (0)} & \mathbb{F} & \xrightarrow{\varphi_1^2 = \begin{pmatrix} 1 \\ 0 \end{pmatrix}} & \mathbb{F}^2 & \xrightarrow{\varphi_2^3 = \begin{pmatrix} 1 & 0 \end{pmatrix}} & \mathbb{F} \end{array}$$

Figure 2: Two persistence modules. The one on the top has interval decomposition  $\{[1, 2], [2, 3]\}$ , while it is  $\{[1, 3], [2, 2]\}$  for the bottom one.

## 2.2 Barcodes

**Definition 2.3** (Interval module). Let  $I \subset T$  be an interval (for instance  $I = [a, b]$ , or  $I = [a, \infty)$  if  $T \subset \mathbb{R}$ ). The *interval module*  $\mathbb{F}^I$  is the persistence module defined by:

- $V_t = \mathbb{F}$  if  $t \in I$ , and  $V_t = 0$  otherwise;
- for  $s \leq t$ ,  $\varphi_s^t$  is:

$$\varphi_s^t = \begin{cases} \text{id}_{\mathbb{F}} & \text{if } s, t \in I, \\ 0 & \text{otherwise.} \end{cases}$$

Intuitively, the module is “on” (one-dimensional) exactly on the interval  $I$ , and zero elsewhere.

**Theorem 2.4** (Structure theorem (informal)). *Under reasonable finiteness assumptions (which are satisfied for homology of finite filtrations), any persistence module  $V$  over  $T \subset \mathbb{R}$  can be decomposed (non-uniquely as a module, but uniquely up to isomorphism) as a direct sum of interval modules:*

$$V \cong \bigoplus_j \mathbb{F}^{I_j}.$$

The multiset of intervals  $\{I_j\}$  is called the barcode of  $V$ .

We will not prove this theorem; instead, we will use it as a guiding picture: each homology class is born at some parameter value (when it appears) and dies at a later value (when it becomes a boundary). Each such class corresponds to an interval  $[b, d)$  in the barcode.

### 2.3 Diagrams

Barcodes are collections of intervals  $[b, d)$  (birth and death times). For interpretation and visualization, it is often convenient to encode them as a discrete multiset of points (or measure) in the plane.

*Remark 2.5* (Tameness). In applications,  $V_t$  is finite-dimensional for each  $t$ . Such persistence modules with this property are called *tame*. Under tameness *only*, no barcode decomposition can be obtained generically, however, the weaker notion of *persistence diagrams* (see below) is still well-defined.

**Definition 2.6** (Persistence diagram as multisets). Let  $V$  be a persistence module decomposed into interval modules  $\mathbb{F}^{[b_j, d_j)}$  and  $\mathbb{F}^{[b_j, \infty)}$ . The  $k$ th persistence diagram (for a fixed homological degree) associated to  $V$  is the multiset of points in the extended plane

$$\text{Dgm}(V) := \{(b_j, d_j) \in \mathbb{R}^2 : \text{finite intervals}\} \cup \{(b_j, \infty) : \text{infinite intervals}\},$$

where each interval  $[b_j, d_j)$  contributes one point of multiplicity 1, and similarly for  $[b_j, \infty)$ .

In practice, one usually plots only finite points  $(b_j, d_j)$  in the half-plane  $\{(b, d) \mid b < d\}$ , sometimes truncating very long intervals, and remembers separately the number of infinite bars. Equivalently, one can see persistence diagrams as purely discrete measures.

**Definition 2.7** (Persistence diagram as measures). Let  $V$  be a persistence module decomposed into interval modules  $\mathbb{F}^{[b_j, d_j)}$  and  $\mathbb{F}^{[b_j, \infty)}$ . The  $k$ th persistence diagram (for a fixed homological degree) associated to  $V$  is the measure on the extended plane

$$\text{Dgm}(V) := \sum_j \delta_{(b_j, d_j)},$$

## 3 Bottleneck distance between diagrams

To compare the shapes of two datasets, or the effect of noise, we need a way to compare persistence diagrams. The standard metric is the *bottleneck distance*.

### 3.1 Definition

Let  $D_1$  and  $D_2$  be two persistence diagrams (thought of as multisets of points in the open half-plane  $\{(b, d) \mid b < d\}$ ). Following the usual convention, we also allow matching points in one diagram to points on the diagonal  $\{(x, x)\}$ , representing intervals of length 0 (i.e. classes that are born and die instantly).

**Definition 3.1** (Bottleneck distance). The *bottleneck distance* between diagrams  $D_1$  and  $D_2$  is

$$d_B(D_1, D_2) := \inf_{\gamma} \sup_{x \in D_1} \|x - \gamma(x)\|_{\infty},$$

where:

- the infimum is taken over all bijections  $\gamma : D_1 \cup \Delta \rightarrow D_2 \cup \Delta$ , where  $\Delta = \{(x, x) : x \in \mathbb{R}\}$  is the diagonal with infinite multiplicity,
- $\|\cdot\|_{\infty}$  is the maximum norm:  $\|(b_1, d_1) - (b_2, d_2)\|_{\infty} = \max(|b_1 - b_2|, |d_1 - d_2|)$ .

Intuitively:

- We match points of  $D_1$  to points of  $D_2$ , or if needed to the diagonal (interpreted as “noise” that can be killed).
- The cost of a matching is the largest shift in birth or death time needed to align corresponding points (measured in  $\|\cdot\|_{\infty}$ ).
- We take the infimum over all matchings.

*Remark 3.2.* Matching a point  $(b, d)$  to the diagonal  $(x, x)$  costs at least  $\frac{d-b}{2}$ , since the closest diagonal point is  $(\frac{b+d}{2}, \frac{b+d}{2})$ . Thus killing a long interval is expensive, while killing a very short interval is cheap.

## 4 Stability of persistence

A crucial property of persistence diagrams is that they are *stable*: small perturbations of the input produce only small changes in the diagrams, measured by the bottleneck distance.

### 4.1 Stability of sublevel set filtrations

Let  $X$  be a compact metric space, and let  $f, g : X \rightarrow \mathbb{R}$  be two continuous functions. For each  $t \in \mathbb{R}$  define the sublevel sets

$$X_t^f := \{x \in X : f(x) \leq t\}, \quad X_t^g := \{x \in X : g(x) \leq t\}.$$

For a fixed homological degree  $k$ , these define two persistence modules:

$$t \mapsto H_k(X_t^f), \quad t \mapsto H_k(X_t^g),$$

and two associated persistence diagrams  $D_k^f$  and  $D_k^g$ .

**Theorem 4.1** (Stability of persistence diagrams for functions). *Let  $X$  be a compact metric space and  $f, g : X \rightarrow \mathbb{R}$  continuous. For each  $k \geq 0$ ,*

$$d_B(D_k^f, D_k^g) \leq \|f - g\|_{\infty},$$

where  $\|f - g\|_{\infty} = \sup_{x \in X} |f(x) - g(x)|$ .

*Idea.* If  $\|f - g\|_{\infty} \leq \varepsilon$ , then for every  $t$ :

$$X_t^f \subset X_{t+\varepsilon}^g \quad \text{and} \quad X_t^g \subset X_{t+\varepsilon}^f.$$

This gives, for each  $k$ , a family of linear maps between the persistence modules shifted by  $\varepsilon$  in both directions. One says that the corresponding modules are  $\varepsilon$ -interleaved. The classification of persistence modules and the definition of bottleneck distance imply that such an interleaving forces the diagrams to be at bottleneck distance at most  $\varepsilon$ .  $\square$

*Remark 4.2.* The precise notion of interleaving is algebraic, but the geometric intuition is simple: if  $f$  and  $g$  differ by at most  $\varepsilon$ , then the sublevel sets at level  $t$  for one function are contained in the sublevel sets at level  $t + \varepsilon$  for the other. Thus the birth and death times of homology classes can only shift by at most  $\varepsilon$ , which is exactly what the bottleneck distance measures.

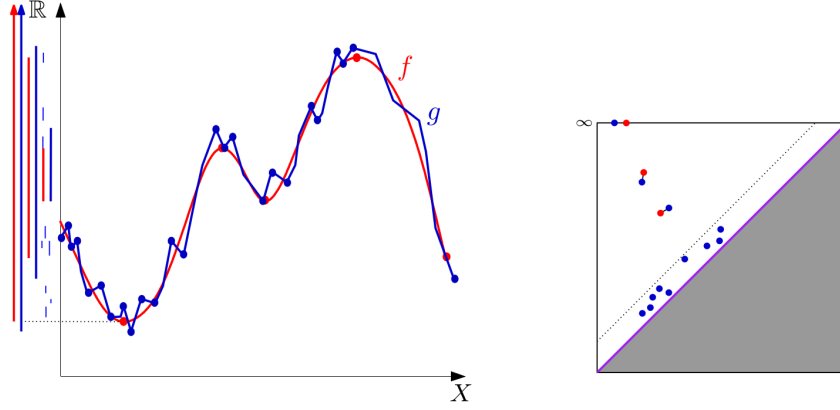


Figure 3: Zeroth order persistent homology of the sublevel sets of two closely functions  $f, g : [0, 1] \rightarrow \mathbb{R}$ .

## 4.2 Stability for point clouds

There are also stability results comparing the persistence diagrams of Rips or Čech filtrations built on finite subsets of a metric space, with respect to the Hausdorff distance between point clouds. We state one very informal version.

**Theorem 4.3** (Informal stability for Rips filtrations). *Let  $P, Q$  be two finite subsets of a metric space  $(M, d)$ , and let  $d_H(P, Q)$  be their Hausdorff distance. Then, for each  $k$ , the persistence diagrams of the Rips filtrations  $\text{Rips}(P, \alpha)$  and  $\text{Rips}(Q, \alpha)$  (built with the same metric  $d$ ) satisfy*

$$d_B(D_k^{\text{Rips}}(P), D_k^{\text{Rips}}(Q)) \leq d_H(P, Q).$$

The message is: if we perturb the point cloud slightly (for instance due to sampling noise), the persistence diagrams change only slightly.